PACTRACK: THE USE OF VIRTUAL ENVIRONMENTS IN THE IDENTIFICATION AND ANALYSIS OF THE NEURONAL CORRELATES OF FEAR, ANXIETY, AND APPROACH-AVOIDANCE BEHAVIORS

Presented by

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PacTrack: The use of virtual environments in the identification and analysis of the neuronal correlates of fear, anxiety, and approach-avoidance behaviors

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Abstract

Electroencephalography (EEG) is a powerful tool that has proven itself essential in successfully discovering significant neuronal correlates underlying various cognitive and behavioral events, such as the hippocampal theta oscillation in memory and spatial navigation. A large negative deflection in potential has been observed as a critical component in modulating error in information processing, termed the ERN. A similar pattern has been found following positive feedback, though whether an analogous effect occurs in internally recognized success is unknown. Researchers have additionally found evidence that theta and gamma oscillations and their intersections play important roles in regulating general fear and anxiety. In this investigation, we study whether a significant deflection in potential occurs as a result of internally recognized success, as well as whether the neuronal correlates associated with fear and memory extend themselves to approach-avoidance behaviors, by observing scalp EEG in midfrontal cortex while playing *Pac-Man*, taking advantage of *Pac-Man's* various behavioral events and states to simulate the above. We find evidence of the ERN following failure, though no significant evoked potential following similar internally recognized success events is observed. The theta and gamma oscillatory patterns modulating fear and anxiety are ascertained to hold true to novel approach-avoidance contexts, and preliminary evidence detecting a shift in oscillations following learning is marked. While EEG is typically performed in laboratory settings, our study shows the merits of and our increasing capability to gather EEG data in naturalistic environments, informing our ability to decode neuronal mechanisms in more everyday contexts and increasing the ethological validity of our work.

1. Introduction

Electroencephalography (EEG) data has often been used to elucidate the neural underpinnings underlying human behavior. Over the past few years, researchers have built up a large body of evidence identifying and analyzing relevant neural correlates to cognitive events, such as the theta oscillation implicated in learning and memory (Kahana et al., 2001; Buzáski, 2005), or the decline in beta oscillatory power involved in voluntary movement (Davis et al., 2012). Extracellular rhythmic field potentials generated by neuronal circuits may propagate and be detected by electrodes at the scalp as EEG data if sufficiently powerful. The detection of EEG at the scalp is itself thus evidence for neural synchrony, lending credence to the fact that is coding for some process significant to the cognitive event at hand (Roach and Mathalon., 2008).

Two main approaches to analyzing EEG data have been proposed and utilized in the field: Event-Related Potential (ERP) analysis and Time-Frequency Analysis. The ERP is a characteristic voltage deflection generated by brain structures time-locked to some sensory, cognitive, or motor stimulus, produced per the averaging of several EEG data epochs around the occurrence of that event, removing background brain activity irrelevant to the stimulus in the process through phase cancellation (Blackwood and Muir, 1990). Thought to reflect the summed postsynaptic potentials of neurons firing in response to an event, analysis of these potentials may offer some insight into information processing with regard to a stimulus (Sur and Sinha, 2002).

Time-Frequency Analysis instead looks to investigate the modulation and synchronization of neuronal oscillations associated with events. This method is quite recent, its use growing rapidly over the past decade, prompted by developments in

neuroscience research indicating the importance of oscillations as mechanisms for systems communication (Roach et al. 2008). Rather than focusing on specific voltage deflections around the stimulus, specific frequencies of the EEG waves and their interactions are examined. Oscillatory analysis has shown distinctive neural correlates of cognitive events, exhibiting characteristic patterns tied to a variety of behaviors. These oscillations have proven to serve important roles in normal neural functioning, able to indicate to us which brain regions are active and essential in the binding and communication of information across the brain (Jacobs and Kahana, 2010).

The ERP has been shown to produce differential amplitudes dependent on the success or failure of an action, tending to exhibit a negative deflection upon error. This characteristic potential is referred to as the "error-related negativity" (ERN) and has been surmised to play key roles in error processing (Falkenstein et al., 1991; Gehring et al., 1993). The signal has been observed and quantified most assuredly over cortical frontal areas, substantiating its proposed mechanism as a tool in error detection (Wessel, 2012). The neuronal generator of the ERN has been identified to be the posterior medial frontal cortex (pMFC), a brain region well associated with cognitive control (Dehaene et al., 1994; Holroyd et al., 1998; Ullsperger and von Cramon, 2001; Gehring and Willoughby, 2002; Van Veen and Carter, 2002; Debener et. al, 2005). In addition to the ERN, a positive deflection peaking ~100-200ms after the erroneous action has been observed as a component of error processing, known as error positivity (Pe, Orr and Carrasco, 2011). Pe has been hypothesized to play a role in indexing the accumulation of evidence that a mistake has occurred, serving as an input to processes that consciously decide whether error had taken place (Steinhauser and Yeung, 2010).

While the manifestation of failure in performance has been well-documented, whether or not significant ERP correlates exist internalizing a success event have been more elusive. An upwards deflection in the ERP following positive feedback, known as reward positivity (RewP) has been reported over the frontal-central regions of the scalp (Holroyd and Coles, 2002; Miltner et. al, 1997). Whether we see a characteristic ERP response following success lacking explicit feedback, however, has not been thoroughly investigated.

Similarly, not well-established are the neural correlates of approach-avoidance behavior in humans. Critical to the survival of many mammalian species is the ability to forage and pursue prey, as well as the capability to respond to incoming threats (Stephens and Krebs, 1986; Ydenberg and Dill, 1986). Given its necessity, it follows that our cognition has likely developed advanced neuronal computations governing the operation. Though its neuronal processes are unknown to us currently, the neuroanatomy of the pathway is more elucidated, with the ventromedial prefrontal cortex (vmPFC) and dorsal anterior cingulate cortex (dACC) implicated in its circuit (Yoo et al., 2020). More specifically, it has been observed that the vmPFC and anterior cingulate are active in the processing of distal threat, while more low-level midbrain areas, such as the periaqueductal gray (PAG), are engaged as the threat grows more proximal (Mobbs et al., 2007).

While we have yet to analyze the neural correlates of predator-prey states themselves, neuronal oscillations have been identified for fear and anxiety, emotions intimately linked with approach-avoidance behaviors (Bocchio and Capogna, 2014). The basolateral amygdala (BLA), hippocampus, and medial prefrontal cortex(mPFC)

comprise a circuit underlying fear and anxiety, and they have been found to exhibit synchronized theta oscillations correlated with fear (Seidenbecher et al., 2003). Theta-coupled gamma oscillations generated in the BLA have additionally been found to be evoked and enhanced by fear stimuli (Courtin et al., 2014). Slow theta oscillations (4-8 Hz), characterized as “emotional” theta, are elicited classically during fear memory retrieval and serve to modulate fast gamma (70-120 Hz) during fear and anxious states (Seidenbecher et al., 2003). During safety states, mPFC driven theta oscillations have been found to be dominant, serving as an input to the BLA to reduce BLA firing (Likhtik et al., 2013). Contrary to expectation, fast gamma power in the BLA and mPFC is increased upon exposure to safety signal, though less coupled to the theta rhythm (Stujenske et al., 2014). Synchronization and timing between theta and gamma oscillations appear to be crucial for the encoding of fear, but less so during safety, manifesting itself instead as an increase in gamma power.

Given its role in fear and anxiety, we hypothesize that the theta and gamma oscillatory patterns underlying fear and safety states should prove generalizable to approach-avoidance behaviors. Here, we investigate whether this holds true using the video game *Pac-Man* to simulate predator and prey relationships. *Pac-Man* allows for states where the player must elude “ghosts” in one condition and where the player is rewarded for hunting those “ghosts” in another, granting it optimal for approach-avoidance analysis. By analyzing the various behavioral events in the game as analogs of several cognitive states, we aim to observe the neuronal correlates of those states and examine whether the canonical evoked potential and oscillatory patterns hold true to this novel context.

2. Materials and Methods

2.1. Pac-Man

We examined the neural activity of one healthy subject human male, aged 22-years old, as he engaged in several sessions of the video game, *Arcade Game Series: Pac- Man*. *Pac-Man* was accessed through Steam, a video game digital distribution interface, on a MacBook Pro laptop utilizing a Windows 10 OS. Five discriminate sessions (n = 5) were played, spaced with several days in between each to ensure neural data remained discrete and to avoid potential modulation by short-term working memory of previous sessions. Each session consisted of ~30 minutes of playtime and comprised of playing several games of *Pac-Man*. Behavioral play data was recorded using the recording function of the Windows 10 Game Bar.

2.2. Input Logging

A custom Python script was designed to keep a running log of keyboard inputs whilst the player was engaged in a session of *Pac-Man*. The script was enabled during the session, and recorded any button press the player inputted onto the keyboard, as well as the time in which that input occurred.

2.3. EEG

EEG data was collected during play sessions of *Pac-Man* using the Muse 2016 headband, designed and produced by InteraXon. The Muse 2016 headband is 4-channel scalp EEG sensor, fitted with 4 electrodes over the International 10- 20 System standard electrode locations anterio-frontal 7 and 8 (AF7 and AF8), temporal-posterior 9

and 10 (TP9 and TP10), as well as with a reference electrode over the fronto-polar midline (Fpz). Originally marketed as biofeedback for meditation, its capabilities have proved it suitable for research.

The EEG data detected by the Muse 2016 headband and was communicated and logged over Bluetooth into the “Mind Monitor” app, developed by James Clutterbuck. The data was sampled at 256 Hz and read into the “Mind Monitor” app with a constant refresh rate. From the “Mind Monitor” app, data was exported as a .csv file, reporting time, raw EEG data, and internally calculated frequency band power per channel. In addition, the user is able to manually input “markers” into the data to denote events of interest, as well as filter out artefactual data as a result of eyeblinks.

2.4. Data Processing and Analysis

2.4.1 EEG Processing

Processing and subsequent analysis of all gathered data was performed on MATLAB R2019a. The raw EEG data was then subjected to a stop Butterworth filter from 58-62 Hz to remove electrical artefacts. Further, the data was high pass Butterworth filtered at 0.5 Hz to eliminate noise. From experimentation, the TP9 and TP10 electrodes were found to be highly susceptible to electronic interference and were deemed unsuitable. The two channels were subsequently removed from further analysis.

2.4.2 Pac-Man Video Processing

Each played session of *Pac-Man* was recorded and further processed to extract relevant behavioral events of interest. To find and track the position of the Player Pac-Man and ghosts throughout the video, we first identified the RGB triplets corresponding to the colors of Pac-Man (yellow) and each ghost (red, cyan, orange, pink). The x- and y- coordinates of Player Pac-Man position per frame were then produced by searching for large “blobs” of yellow within the frame, isolating the largest “blob”, and recording its position. A “blob” was defined as continuous clusters of pixels matching the corresponding RGB triplet above a certain threshold. The x- and y- coordinates of the ghosts were identified much the same way, identifying large “blobs” of each ghosts’ respective color. There is an added caveat with these not present with Pac-Man, being that the ghosts often change color over the course of the game as they shift to a “prey” state. This was rectified in the algorithm by informing it to search for the respective RGB triplets for blue and white (the “prey” ghosts’ colors) if it did not find all four of the “predator” ghosts in the scan of the frame. In addition to ghost position, ghost type (“predator” or “prey”) for each ghost per frame was noted and logged by counting the RGB triplets and number of color “blobs” within that frame.

In addition, we kept track of player deaths throughout each section, recording the number of lives per frame of the video. This was done by first isolating the entire captured frame to only a single region of interest around the number of lives and further employing the same method as for position, finding large “blobs” of yellow and denoting their coordinates. The number of these found coordinates were then registered, this being equivalent to the number of lives at that frame.

Another variable of interest was the score achieved by the player as they progressed through *Pac-Man.* A region of interest containing the score was first identified and isolated within the frame. Optical character recognition was then utilized to extract present numerical characters through the video, corresponding to player score.

2.4.3. Data Synchronization

Three different sources of data were employed and made use of in this experiment, those being the sessions of recorded *Pac-Man* play video, the input log tracking keyboard presses, and the EEG data from the Muse 2016 headband. Each individual source was discrete from the other and were not inherently linked. Additionally, time was logged with each's respective internal clocks, and was thus subject to temporal drift across sources. Thus, synchronization between all three was necessary for appropriate and accurate analysis of brain signals.

This was accomplished by first reconciling the temporal inconsistencies as a result of drift between the input log and EEG data. With the input log script running while recording data from the Muse 2016 headband, the "Mind Monitor" app was used to manually input markers whilst simultaneously pressing the spacebar button on the keyboard before a session of play. The spacebar key was chosen as *Pac-Man* does not utilize the command during gameplay. Doing so yields the time recorded during these paired events for each source. A linear regression was then performed on the times recorded for these matched inputs and resulted in a correcting conversion factor between the EEG data and input log, synchronizing the two sources of data.

Further, we connected the now linked input log to the recorded *Pac-Man* video. During the experiment, we ensured the video recording would begin just as the first game of *Pac-Man* was initiated, requiring the input of the “enter” key in the game. As a result, the first instance of “enter” in the input log data would correspond to the beginning of the *Pac-Man* video. The elapsed duration per frame was extracted and added to the “enter” time in the input log, yielding the time each frame occurred in input log space. Applying the previously attained correcting conversion factor to these times resulted in the equivalent times in the EEG data where each frame occurred. The end result of this synchronization allows us to analyze the neural activity of relevant behavioral events in the *Pac-Man* video.

2.4.4. ERP Analysis

ERPs were extracted around “failure” and “success” events in the game. Failure events were defined as the loss of a life, while success events were those when the player Pac-Man would successfully hunt a ghost or eat a reward fruit item.

The failure events were first established from the *Pac-Man* video through identification of the frames where the number of lives were detected to decrease by 1. The elapsed duration of those frames was isolated, and 3 seconds were subtracted from these durations. This was done to capture the actual onset of player death, as 3 seconds pass before the number of lives are updated to reflect this event. These durations were added to the “enter” time in the input log signaling the beginning of the video and were applied the correcting conversion factor to discern these times in the EEG data. An arbitrary 200 ms pre-event and 800 ms post-event window were

determined to be sufficient for analysis, and the EEG data around those times were extracted and averaged across all failure events.

Success events were established to be points where the player score increased by over 50 points, corresponding to when ghosts were successfully hunted, or a reward fruit was eaten. ERP calculation then followed similarly to the above, identifying these frames from the *Pac-Man* video and recording their durations. Durations were added to the "enter" start time and the correcting conversion factor subsequently applied. EEG data spanning 200 ms and 800 ms after these onset times were gathered and averaged across all success events.

2.4.5. Time-Frequency Analysis

The Oscillatory Reconstruction Algorithm (ORCA) was used to calculate for oscillatory power across frequency bands in the EEG data. ORCA, developed by Andrew Watrous, Ph.D., is an adaptive spectral decomposition algorithm that has been shown to increase the accuracy of identified frequency content (Watrous and Buchanan, 2019). Classically, canonical frequency bands (e.g. beta, 12-30Hz) have been utilized as classifiers of neural activity. However, the frequency of neuronal oscillations has been shown to be variable across tasks to better support the cognitive and behavioral events at hand (Watrous et. al, 2013; Cohen 2014; Samaha et. al, 2017; Furman et al., 2018) and across subjects (Zhang et al., 2018). The use of ORCA allows for adaptive identification of characteristic frequency bands, improving our ability to link significant neuronal correlates to cognitive and behavioral tasks (Watrous and Buchanan, 2019).

We then parsed all frames in the *Pac-Man* video into two separate conditions, the "avoid" state and the "approach" state. The avoid condition was specified to be points where ghosts were in the "predator" state and actively chasing the player Pac-Man. The approach condition, meanwhile, was specified to be periods where the ghosts were in the "prey" phase and could be hunted. The division was performed by analyzing the type of the ghost per frame and assigning those frames to the appropriate condition. The elapsed duration of each frame in the two conditions were added to the "enter" start time and treated with the correcting conversion factor to yield a set of times in the EEG data where the player was avoiding, and another where the player could approach. We then assigned the power of each frequency band at each point in time to their respective avoid or approach conditions. A two-sample t-test at each frequency band within a channel was further performed to analyze whether oscillatory power of the two conditions significantly deviated from one another.

3. Results

3.1. ERP Results

Fig. 1(a) and (b) show the results of the ERP analysis time-locked to either failure or success events for channels AF7 and AF8, respectively. ERPs averaged were averaged around 63 failure events and show in AF7 the characteristic downward deflection exhibited in ERN peaking 200 ms after event onset. These AF7 failure ERPs additionally show a period of sustained large positive deflections, similar to the Pe wave we expect to see following ERN. The failure ERPs for AF8 do not show the voltage

deflections representative of the ERN, instead showing large, wide ranges of negative deflections peaking at event onset and 600 ms after. The failure ERP in AF8 also shows a large positive deflection around from 200-400 ms after the failure onset. Success ERPs, averaged around 792 successful events, do not show any deviation from normal in both AF7 and AF8.

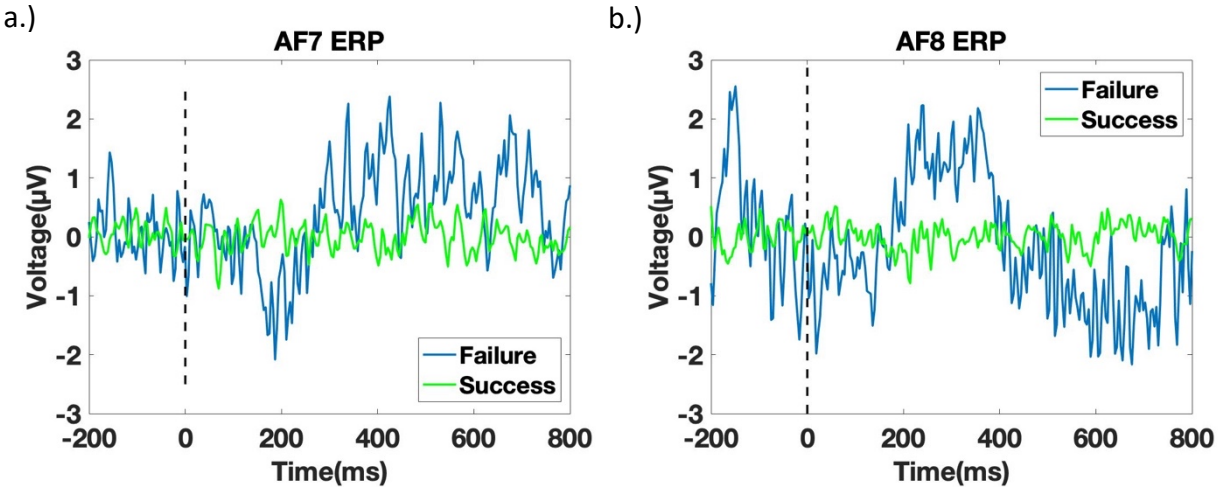

Fig. 1. - Averaged ERPs for the (a) AF7 channel and (b) AF8 channel. Blue ERPs represent evoked potentials averaged over all failure events, and green ERPs represent those averaged over all success events. Dashed line signifies onset time of each's respective event.

3.2 Time-Frequency Results

Fig. 2(a) and (b) represent amplitudes throughout ORCA found frequency bands comparing across avoid and approach conditions during session 1 for channels AF7 and AF8, respectively. We note a significant difference in avoid and approach amplitudes in AF7 for oscillations in the 0.5-4 Hz, 4-8 Hz, and 12-30 Hz frequency

bands (t = 8.6916, p < 0.05; t = 6.0729, p < 0.05; t = -3.2502, p < 0.05; Bonferroni corrected). Significance in AF8 is observed over the 0.5 – 4 Hz (t = 2.8775, p < 0.05, Bonferroni corrected) and 4-8 Hz (t = 3.1499, p < 0.05, Bonferroni corrected) frequency bands. We observe in both channels that low frequency oscillations are prevalent during avoid conditions, whereas high frequency oscillations increase in power during approach states. Canonical alpha power, at 8-12 Hz, is lowest in amplitude across both conditions. This same general trend is found across all sessions, as substantiated with session 3 in Fig. 3.

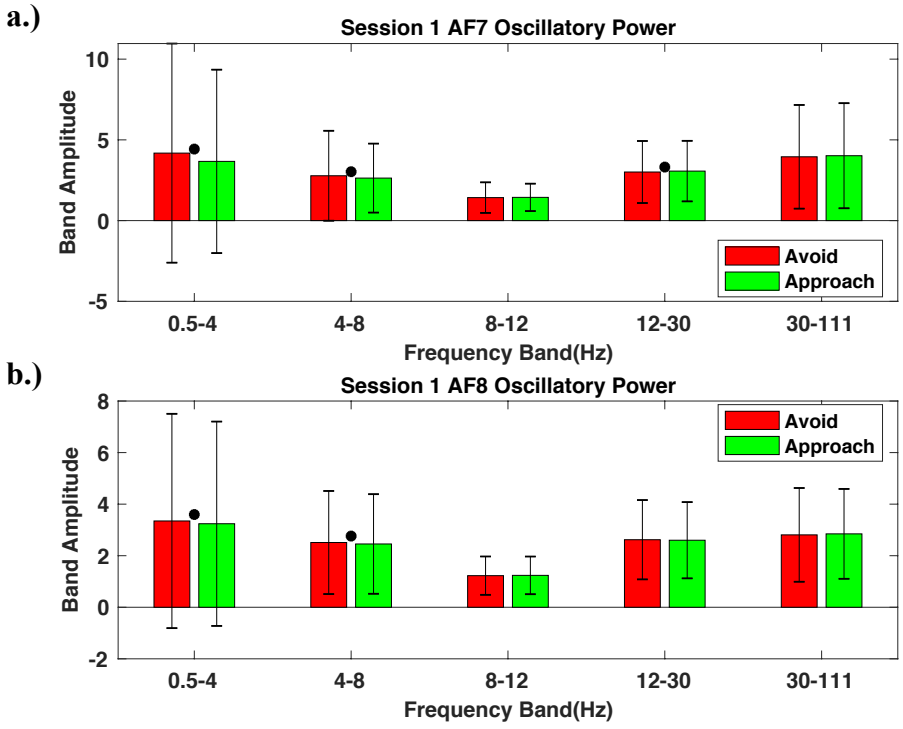

Fig. 2. - A comparison of approach vs. avoidance oscillatory power during session 1 across frequency bands for (a) AF7 and (b) AF8. Red bars signify avoid mean amplitudes, while green bars represent approach condition mean amplitudes. Error bars represent standard deviation of band amplitudes, while an

asterisk denotes a significant difference in power between approach and avoid conditions (α=0.5, Bonferroni corrected).

Fig.3 (a) and (b) communicate oscillatory power between approach and avoid conditions across frequency bands for channels AF7 and AF8, respectively. A significant difference in oscillatory amplitude between conditions in AF7 is found in the 0.5-4 Hz frequency band (t = 17.8145, p < 0.05, Bonferroni corrected). Session 3 AF8 oscillatory power sees significant differences between avoid and approach states in the 0.5-4 Hz, 4-8 Hz, and 30-111 Hz frequency bands (t = 15.4757, p < 0.05; t = 3.9774, p < 0.05; t = -2.7251, p < 0.05; Bonferroni corrected). While frequency bands of significance differ between sessions 1 and 3, the same patterns are observed, in that high frequency band power prevails in the approach condition, while low frequency oscillations increase in power in avoidance states. The 8-12 Hz rhythm remains a lower amplitude compared across frequency bands. These same trends are repeated across sessions, as may be observed in the Supplemental Figures. Of note is that AF7 in session 4 shows two frequency bands through ORCA but follows the same general pattern as the above (Supplemental Figures). Session 4 AF8 similarly shows frequency bands different to the canonical, though still five in number (Supplemental Figures). The singular exception to the general trend lies in AF8 session 5. Shown in Fig.4, adaptive spectral decomposition through ORCA found three frequency bands: 0.5-13.9 Hz, 13.9-55.6 Hz, and 55.6-111 Hz, all of which show significant differences between conditions (t = -5.9221, p < 0.05; t = -10.065, p < 0.05; t = -5.3749, p < 0.05; Bonferroni corrected).

Session 5 AF8 shows oscillatory power higher in the approach condition across all frequency bands.

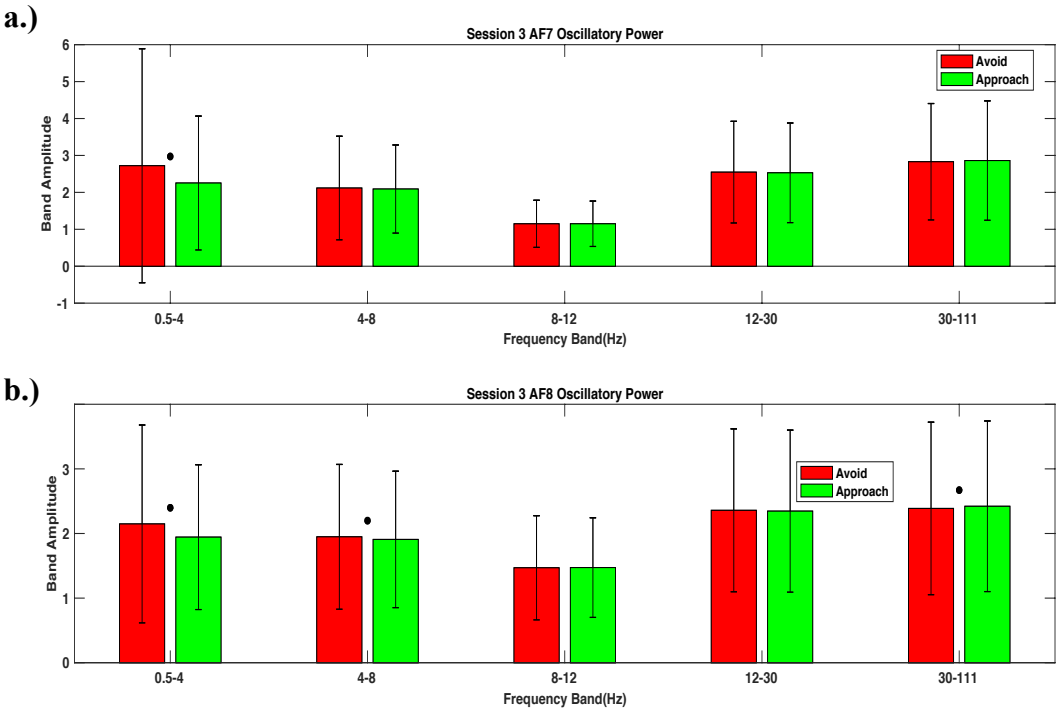

Fig. 3. - Approach vs avoidance oscillatory power during session 3 across frequency bands for (a) AF7 and (b) AF8. Red bars represent mean amplitudes during avoidance conditions, while approach state oscillatory power is expressed by green bars. Asterisk denotes significant differences in oscillatory amplitude between conditions (α = 0.5, Bonferroni corrected), and standard deviations of band amplitudes are represented by error bars.

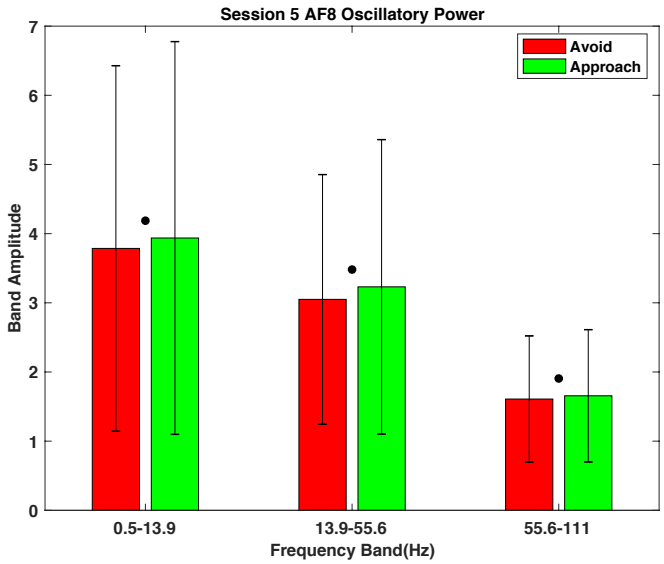

Fig. 4. - Oscillatory power in AF8 between avoid and approach conditions during session 5. Avoid states are represented by red bars, and green bars constitute the approach condition. Asterisks denote significance in oscillatory amplitude difference between the conditions at each frequency band (α = 0.5, Bonferroni corrected). Error bars constitute standard deviations of band amplitudes.

4. Discussion

We attempted in this study to explicate the neuronal correlates of approach-avoidance behaviors through the use of *Pac-Man*'s implicit predator-prey relationships, as well as observe whether canonical evoked potential and oscillatory patterns would remain valid in this novel context. The participant subject engaged in five discrete, 30-minute sessions of *Arcade Game Series: Pac-Man*, and his neural data investigated.

Evoked ERPs were extracted around loss of life events (deemed “failure”) and around large increases in score (deemed “success). Assessing channel AF7, we see the failure ERP exhibit the voltage deflections characteristic of ERN, with a negative deflection near event onset followed by the Pe component (Falkenstein et al., 1991; Gehring et al., 1993; Orr and Carrasco, 2011). The negative voltage deflection of the ERN typically occurs right at event onset, while here, we see it peak at 200 ms after. This may be in part due to the fact that the video frame does not shift to reflect the player death until a few seconds after death has occurred. We estimated this time delay to be 3 seconds upon inspection and adjusted the analysis as such. However, given the temporal scale the ERN operates, some small deviation for those 3 seconds (say, the time delay was actually 2.9 seconds) would shift the waveform. Interestingly, the ERPs around failure events evinced by channel AF8 show a different story. AF8 failure ERPs instead display wide, interspersed negative and positive voltage deflections. This finding may suggest differential roles of brain hemispheres in error processing outside of a lab environment, with the right frontal lobe perhaps modulating the error feedback governed by the left frontal lobe. ERPs have shown themselves them to be rather variable both within and across subjects, however, so more research must be conducted to further investigate before this may be substantiated. ERPs around success events see no appreciable deviation from baseline. Previous research has shown that RewP is manifested in the ERP after positive feedback (Holroyd and Coles, 2002; Miltner et. al, 1997). RewP is typically found after the receival of positive confirmation of some form of unknown choice. The fact that we do not see evidence of RewP or anything similar indicates to us that its function is to underlie positive learning after explicit feedback. In

Pac-Man, the player expects the large increases in score after corresponding success events, and no learning is involved in the process. Investigating these success ERPs in individuals who have no prior knowledge of *Pac-Man* may serve as an avenue to test this hypothesis.

We hypothesized that the neural correlates observed in fear and anxiety may prove themselves to be applicable to approach-avoidance behaviors. Oscillatory analysis during “predator” and “prey” phases of *Pac-Man* reveal this may be the case. Oscillations at classical theta frequencies have shown to be prevalent during fear memory retrieval and anxious states (Seidenbecher et al., 2003). Fear and anxiety are emotions involved in predator avoidance, and thus the avoidance condition in our experiment should show these increases in theta power. Our findings show this result, with low frequency oscillations dominant in the avoidance phase, consistent across channels and sessions. In *Pac-Man*, phases where the player is able to hunt ghosts remove predatory threat and should therefore represent security in the individual. Safety states have been found to be correlated with an increase in gamma power as theta-gamma coupling becomes less prevalent (Stujenske et al., 2014). We similarly find that our data is consistent with this result, displaying increased power in high frequency oscillations during the approach phase. One instance, being session 5 in channel AF8, shows deviations from these general results, in that oscillations in all frequency bands are dominant through all approach phases. While preliminary, this may be evidence that frontal right hemisphere may play more modulatory roles outside of lab settings as a function of more naturalistic environmental variables, similar to the failure ERP we observed in AF8. Adaptive spectral decomposition on this channel in session 5 shows

characteristic action in three different frequency bands, compared to the classically defined five canonical frequency bands, which further implicates it may be playing a role different from governing fear and anxiety. The fact that this occurs in session 5 may speak to this result being due to learning and acclimating to *Pac-Man* and its approach-avoidance states. Perhaps relevant brain areas are devoted to controlling fear and anxiety until learned, at which point some of those brain areas switch to play a more regulatory function. This is supported by Session 4, another session in the latter half of playtime, where adaptive spectral decomposition in both channels AF7 and AF8 sport frequency bands unique from the canonically defined bands, possibly suggesting some unique function aside from fear and anxiety control. Playing more sessions and analyzing the frequency bands found in those sessions is necessary to begin observing whether that hypothesis is valid.

Of importance is that our study shows our increasing capability and potential to attain and analyze information about the brain in more natural settings. Typically, EEG data is gathered in and under laboratory conditions. This artificially adjusts the environment and may introduce fluctuations in brain activity due to variables present in the lab absent in everyday settings, such as, but not limited to, the Hawthorne effect, not truly simulating activity during normal behavior. (McCambridge et al., 2014). Analysis of EEG data taken in more native settings will help to elucidate the mechanisms of the brain as it typically functions from the day-to-day, increasing the ethological validity of found neuronal correlates of behavior. Our experiment was conducted outside of the laboratory and required only an EEG headband to collect data. We were able to find with our results proof of previously found and commonly accepted

neuronal correlates, such as the ERN and theta-gamma oscillations involved in fear and anxiety, corroborating that data taken in this way seems to be valid. Our preliminary findings showing hemispherical differences in the ERN and the evolution of oscillatory power over time show that this method holds promise and may begin to provide insights not able to be gleaned in typical laboratory settings.

Supplemental Figures

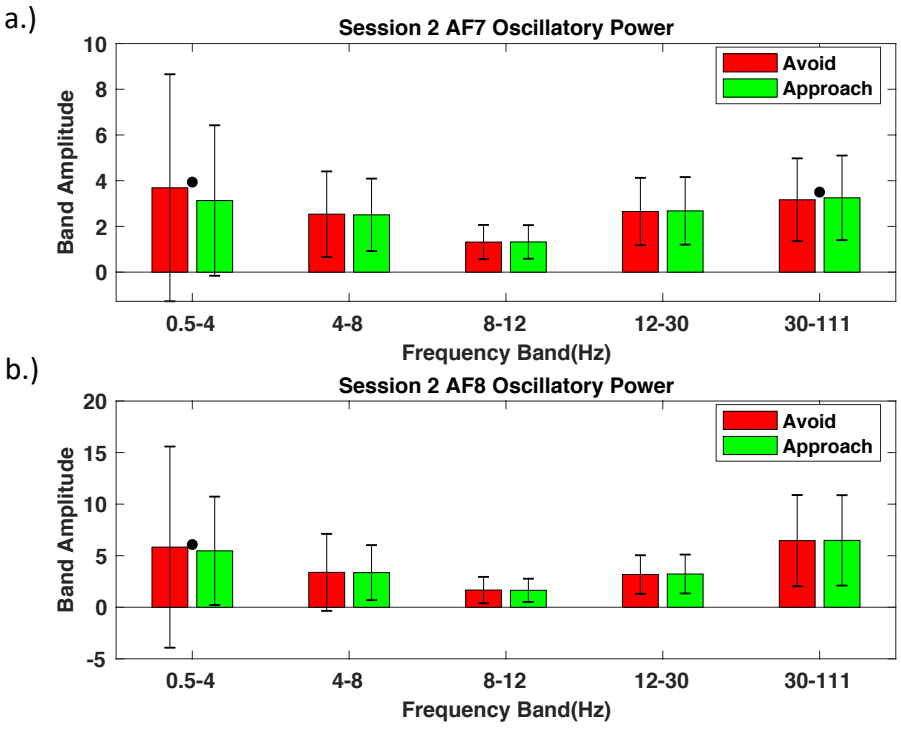

Fig. S1. - Comparison of oscillatory power in approach and avoidance states across frequency bands during session 2 in (a) AF7 and (b) AF8. Mean band amplitudes are reported as bars, with the green bars signifying approach

condition oscillations and red bars indicating avoid condition oscillations. Error bars constitute standard deviations of band amplitudes, and an asterisk denotes a significant difference between conditions in the respective frequency band (α = 0.05, Bonferroni corrected).

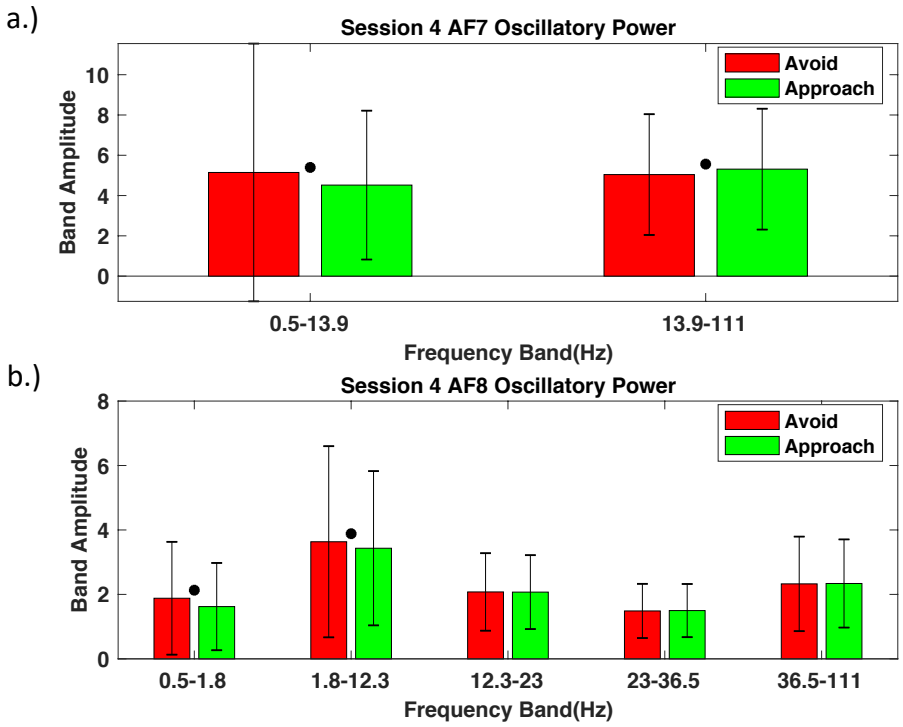

Fig. S2. - Oscillatory power during session 4 in channels (a) AF7 and (b) AF8 across frequency bands. Red bars indicate mean band amplitudes for the avoid condition, while the mean band amplitude in the approach state is represented by green bars. Error bars show the standard deviations of band amplitudes. A significant difference between states is marked by an asterisk (α = 0.5, Bonferroni corrected).

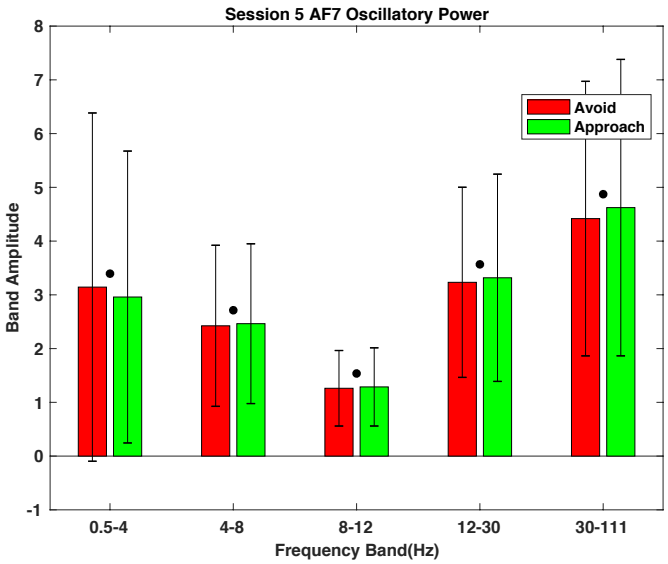

Fig. S3. - Session 5 oscillatory power in channel AF7, compared between approach and avoidance states across frequency bands. Bars show mean band amplitudes, with conditions indicated by bar color. Error bars report the standard deviations of band amplitudes, and an asterisk identifies a significant difference between states in respective frequency bands (α = 0.5, Bonferroni corrected).

Acknowledgements

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